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Research Article

Optimization and Analysis of Raw Material Supply Chain Based on Computational Intelligence

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With the rapid economic growth and increasingly fierce market competition, the traditional manufacturing advantages have become a thing of the past. There are problems such as inaccurate procurement plans, large quantities of inventory sold out, chaotic procurement processes, and unclear inventory policies. Optimizing the procurement of basic raw materials will help reduce raw material costs. This paper analyzes some raw material supply chain processes through the Delphi method, Plato principle, and trend-adjusted exponential smoothing method and finds that the important factors for improving raw material supply include economic and technological environment, the realization of purchasing department functions, price stability, technical level, system management awareness, product qualification rate, quality inspection and testing, and problem handling timeliness. Financial situation, procurement efficiency, and cooperation compatibility are important factors for improving the supply of raw materials. By using key indicators to select strategic suppliers and computational intelligence to obtain the forecast value of raw material supply, the forecast error rate is within 9%, indicating that the forecast data are reliable and can be used as an auxiliary tool for raw material supply, thereby reducing risks. Under the corresponding conditions, the waste of raw materials can be reduced and the raw materials can be stored more reasonably. Using the Delphi method, Plato principle, and trend adjustment exponential smoothing method to analyze part of the raw material supply chain process brings benefits to the enterprise and finally achieves the standardization of the procurement process, the optimization of supplier groups, the sharing of procurement information, the supervision of procurement process, the reduction of purchasing costs, improvement of procurement intelligence, division of labor and performance assessment, and achievement of a win-win situation with suppliers.

1. Introduction

This study discusses the issue of integrated supply chain optimization that optimizes facility location, customer allocation, and inventory management when a business is at risk. When a facility fails, its customers can move to other operating facilities to avoid heavy loss of service penalties. The problem is formulated as nonlinear mixed integer programming to minimize the sum of the expected total costs. The model simultaneously determines the location of the distribution center and assigns the affected customers to the distribution center location. In order to solve the proposed model, an efficient solution method is based on the p-Resented genetic algorithm. Finally, the calculation results of several cases of this problem are presented, verifying the effectiveness of the proposed model and algorithm [1]. The use of computational intelligence methods is described to forecast supply chain demand. In particular, we pay attention to supply chains directly related to forecasting customer demand in an uncertain environment. Anticipating expected demand for one or more products over time is the main goal of the company because it directly affects revenue and customer satisfaction. Therefore, we use artificial neural networks (ANN) and support vector machines (SVM) as demand forecasting methods to build a supply chain structure with dynamic functions. In the following section, we will look at previous research on forecasting demand in SC using computational intelligence techniques. Then, we analytically describe the techniques used in the current works [2]. The paper provides a mathematical model that considers the limits of the spoilage (perishable materials) of raw materials and falls within the category of NPhard problems. Ant colony optimization (ACO) and particle swarm optimization (PSO) are applied to solve the proposed model. In order to improve the performance of the ACO and PSO parameters, the Taguchi Design of Experiments method was applied to set their appropriate values. Furthermore, to evaluate the performance of the proposed model, an example from the dairy industry is analyzed using MATLAB *R* 2015a. In order to validate the proposed metaheuristics, their results are compared. The comparison results show that ACO is faster than PSO [3] in both the speed of convergence and the number of solution iterations. This chapter addresses the issue of balancing and optimizing the multi-tiered supply chain network of an Australian ASX 50 company specializing in the manufacture of agrochemicals. We propose two approaches to drive simulations to determine the quality of the generated solutions: an event-based approach and a fuzzy rule-based approach. As they can generate efficient plans, the rule-based approach significantly outperforms the event-based approach in terms of convergence time and solution quality [4]. The study reviews the techniques and methods of supply chain inventory optimization and summarizes the commonly used inventory optimization algorithms: mathematical analysis and heuristic algorithms. Finally, several key factors of supply chain inventory optimization—lead time, enterprise credit, and the degree of ambiguity of some parameters in the optimization process—are pointed out, and their trends are pointed out [5]. In this study, a new two-layer particle swarm optimization algorithm is proposed to solve two known supply chain management problems, which means that vehicle and location routings are problematic. The results of the algorithm are compared to those of algorithms that solve these problems using a single objective function and a two-layer genetic algorithm. Because most decisions in supply chain management are made at different levels, the research presented in this paper has two main goals: providing decision-makers with the possibility to formulate supply chain management problems as two-layer or multi-layer problems and the second proposing an efficient nature-inspired algorithm to solve such problems [6]. Supply chain managers try to maximize the profitable operations of their manufacturing and distribution supply chains, but it is very difficult to optimize supply chain management (SCM) due to the global competition in the process industries, the complexity of supply chain processes, and the large amount of computing time. Therefore, this paper deploys Pinch analysis, a practical tool that requires less complex mathematics than many other optimization tools to manage the critical knowledge generated in the supply chain. In this study, explicit knowledge of demand and supply from an organization is represented as a composite of pinch analysis. The developed system provides supply chain managers with new insights into SCM, which, in turn, facilitates quick decision-making and, in general, contributes to the much-needed competitive advantage [7]. A system is proposed to help define optimization models by regression analysis. This approach aims to gather as much knowledge as possible about the problem so that the duty of optimizing the model definition requires less user involvement. The application of the proposed algorithm will save nearly 1,000 person-weeks on the completion of the project. The developed strategy was applied to the problem of optimizing Caterpillar's global supply chain. The study also describes the procedure of developing an optimized institution for Caterpillar and highlights the challenges and examination opportunities identified during the work, describing an optimization model designed for Ca [8]. The entire supply chain, the inventory of products and materials, and the logistics routes of product supply can be optimized. Supply chain optimization systems and methods for optimizing supply chains are calculated by simulation, in which a supply chain model is used such that the sum of the inventory costs of products and materials and their logistics costs are minimized relative to the inventory quantity. The inventory products increase with fluctuations in the sales plan. In the event that fluctuating times in the sales schedule do not result in product defects, products and materials are set to factory inventory. Also, set inventory quantity, inventory cost, and logistics cost as KPIs for the supply chain you want to manage. In addition, the logistics routes of factories with increased inventory products are optimized by simulation [9]. The method of delivering reports on improving supply chain performance may include generating a view of the organization's supply chain, where the view is generated in response to the identification of supply chain entities and related flows between them. Processes can include transaction-level activities at the SKU level. The method may further refer to a representation to define data grouping based on supply chain contracts, establish master data and one or more scenarios, and use the defined data groups to perform a test against one or more scenarios using processing circuits to generate correlations with baseline performance results [10]. This paper aims to identify gaps in multiobjective optimization- (MOO-) based decision support for make-to-order supply chain management (BTO-SCM). To this end, it reviews the existing literature on build-to-order supply Bespoke Supply Chain Modeling (BTO-SC) to adopt MOO technology as an idea assistance tool. The literature is categorized according to the living of decisions in distinct parts of the provide chain and key decision areas detailed in a typical BTO-SC. It also identifies available software packages supporting BTO decisions in the supply chain and presents appropriate solutions. The gap between the modeling and optimization techniques developed in the literature and the decision support needed in practice is emphasized. The possibility of making better use of MOO decision support puts forward the future research direction [11]. Thiel and Horwitz describe the importance of supply chain optimization to improve healthcare value, focusing on minimizing medical waste. Previous research has shown that physician usage is a major driver of low-value services: variability in surgical supplies usage can lead to a 20-fold difference in cost categories for the same procedure [12]. Aiming at the status quo and the existing problems in managing the optimization of supply chain storage, a new method of genetic optimization of supply chain storage based on complex gradient arithmetic is proposed. The method combines the fast convergence of gradient methods with the powerful search capabilities of local and global genetic algorithms for optimizing storage problems in supply chains. The research results show that the method is effective and applicable [13]. The data explosion that accompanies the problem of the knowledge deficit is becoming more and more apparent. By using business intelligence techniques, supply chain analytics transform data into business insights and optimize supply chain management decisions. This document first describes the BI layers, explains the structure of the supply chain analysis topics, and then explains the details of each topic analysis [14]. This book presents logistics, supply chain management, and applications of evolutionary computing, focusing on specific areas related to supply chain problems, from strategic purchasing decisions, production planning, and control to inventory to logistics and their applications using evolutionary/heuristic techniques. This interdisciplinary book bridges the gap between management research, decision-making, and computer analysis, providing state-of-the-art descriptions of corresponding problems and advanced approaches to solving them [15].

2. Raw Material Supply Chain

2.1. Raw Material Supply Chain Process. Before supplying raw materials, the company usually makes a customized plan for the entire process and then implements the relevant raw material supply plan. Usually, according to the demand for raw materials, the procurement plan is classified by category, and the procurement plan is then submitted to the relevant department for approval and then based on the raw material demand. Purchasing plans calculate relevant raw material price expenditures, strive to reduce expenditures and ensure quality, then select suppliers according to these plans, and finally determine suppliers to supply materials. The process of raw materials from procurement to use is shown in Figure 1.

2.2. Status Quo of Raw Material Supply Chain. First, many SMEs use traditional detriment methods and do not have a complete procurement management system and process. In daily procurement, the procurement of various raw materials cannot be standardized and strictly implemented. The second is the lack of an intelligent platform, the selection of suppliers is not rigorous, the indicators are not comprehensive, and the information transmission between the suppliers and suppliers is poor. In addition, it is difficult for enterprises to grasp the changes in the market, which will lead to the accumulation of inventory. Third, the management of business connection and data exchange is not perfect, resulting in logistics information. Funds do not flow in an orderly manner in the supply chain, payment and pickup are disconnected during the checkout process, and the flow of funds is not very smooth. Data processing can only be recorded afterward and cannot dynamically reflect the state of enterprise operations in real time.

2.3. Importance of Raw Material Supply Chain. As an important link in the high-tech industry chain, raw materials play a supporting and leading role in the development of strategic emerging industries. Security of supply has become one of the most important directions in the system of the world's largest economy. Raw material companies must pay full attention to this. Supply chain construction realizes the commercial digital upgrade of the supply chain management platform and comprehensively enhances the core competitiveness of enterprises. In order to meet the needs of enterprise development, it is necessary to fully consider the cost. During the development process, the profit rate of commodity production will increase, and the enterprise producing commodities will also obtain greater profits. Therefore, in order to improve profit margins, paying attention to the procurement of raw materials is a link that enterprises should pay attention to when manufacturing goods. Selecting profitable raw materials can reduce the capital expenditure of purchasing raw materials on the one hand and improve the product quality and competitiveness of the company on the other hand. In order to stabilize the supply and demand relationship, companies need to transform a simple buying and selling relationship with raw material suppliers into a strategic partnership between companies. Such views and viewpoints are actually from the perspective of the supply chain. By establishing mutually beneficial relationships with suppliers, companies can gain an advantage in the fierce market competition. It is known that in recent years, with the advancement of reform and opening up, more and more enterprises have appeared in China. These companies range in size from medium to small. Regardless of the size of the company, entrepreneurs are very concerned about the internal management of the company and the cooperation with the outside world. The cooperation mode of the enterprise includes the raw material supply mode, the processing mode of the goods, the storage mode of the goods, the quality supervision mode of the goods, and the distribution mode of the goods. Among the many business development models, it is most effective to focus on business development from a supply chain perspective.

As an important link in the high-tech industry chain, raw materials play a supporting, leading, and subversive role in the development of strategic emerging industries, and their supply security has become one of the key layout directions of the world's major economies. Raw material enterprises need to pay full attention to supply chain construction and realize the commercial digital upgrade of the supply chain management platform to comprehensively enhance the core competitiveness of enterprises, increase profit margins, and reduce costs.

2.4. Optimization of Raw Material Supply Chain. In order to realize the computerization of raw material procurement required by market development, an intelligent computer system for optimizing the raw material supply chain was constructed and implemented. The raw material supply chain system relies on scientific and rational planning, organization, coordination and control of the logistics, information flow, capital flow, value-added flow, business flow, and the relationship between suppliers and production facilities in the process of raw material procurement. Integrate the entire system of the enterprise procurement

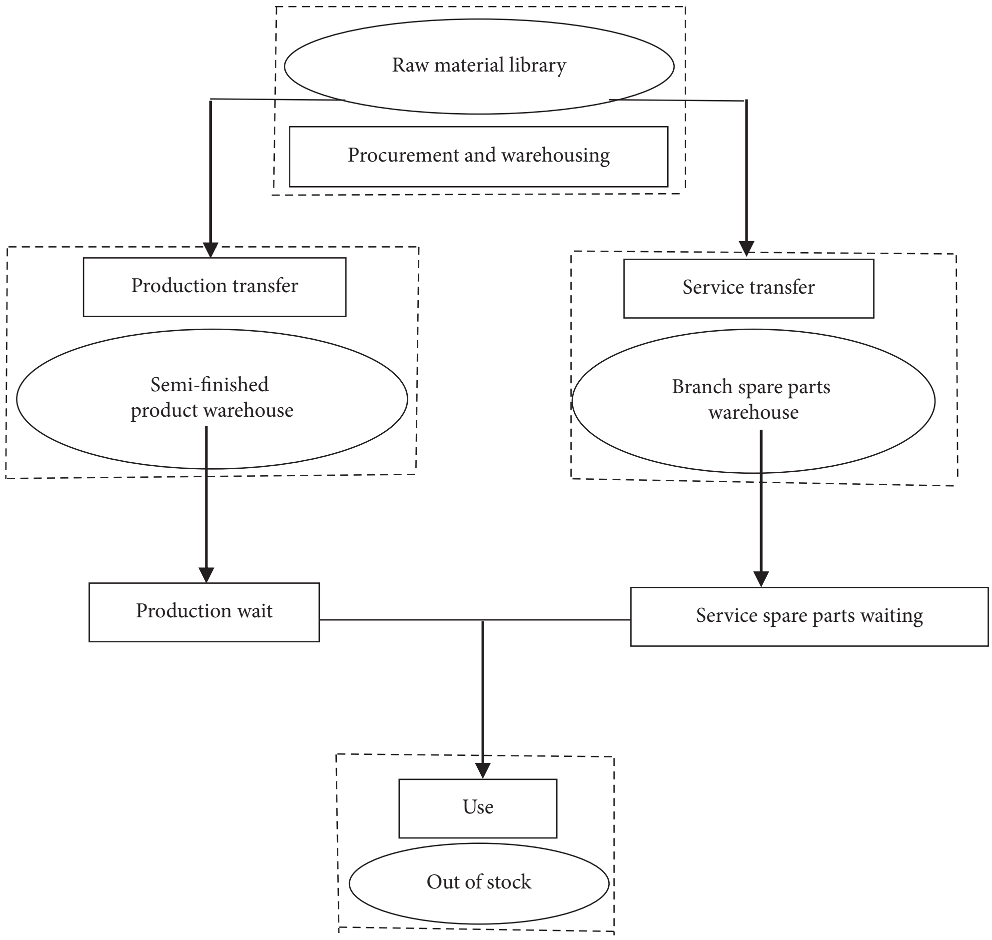

Figure 1: The process of raw materials from procurement to use.

process, such as planning, procurement, underwriting, delivery, inventory, and delivery, so that information can flow smoothly in all aspects of the procurement process and improve work efficiency. At the same time, providing information and rationally using and allocating resources will benefit the enterprise and finally realize the standardization of the procurement process, the optimization of the supplier group, the sharing of procurement information, and the supervision of procurement. Process; reduce procurement costs; improve procurement intelligence, division of labor, and performance appraisal; and achieve a win-win goal with suppliers. Raw material procurement is not a simple raw material procurement process. It is a complex system of functional management, asset management, continuous improvement, and delivery. The functional role and influence of the process's subsystem, as a theoretical guide, can make the management's thinking on the raw material procurement system clearer, the vision more comprehensive, and the operation more efficient.

3. Computationally Intelligent Raw Material Supply Chain

3.1. Delphi Method. According to the Delphi method, the main evaluation indicators should be selected from a qualitative point of view when selecting suppliers. After selecting the KPI, scientific and feasible methods should be adopted to comprehensively calculate the actual supplier procurement management data. Relevant strategic suppliers should be identified. Once selected, the most suitable suppliers are selected based on a weighted index score model for key metrics. The calculation steps of key indicators are presented below.

Assign weights Ki to the indicator performance measurement values, where i represents the i-th key indicator. Score the key indicator performance of each supplier, Pi. Multiply each performance score by its weight to calculate the total score for all KPIs for each supplier:

$$T = \sum_{i=1}^{n} KiPi. \tag{1}$$

Compare the t-values of different suppliers, and select strategic suppliers according to the assignment conditions. When the ten-point or hundred-point system is used for scoring, the arithmetic average Mi value is 0–10 or 0–100 points. The greater the relative importance.

M_j is the arithmetic mean of the scores for j objects, m_j is the number of experts participating in the evaluation of object j, andc_{ij}- is rating for j object:

$$M_j = \frac{1}{m_j}\sum_{i=1}^{m_j} c_{ij}. \quad (2)$$

That means the ratio of the number of experts who evaluate an object as full marks to the total number of experts who evaluate the object. K_j^1 is the full frequency of object j, m_j^1 is the number of experts who have full marks for object j, and m_j is the number of experts who have rated object j. Objects get a full score K_j. The value is 0–1. The larger the value is, the more experts give the object full marks, that is, the greater the relative importance of the object.

It is the ratio of the number of experts who evaluate an object as full marks to the total number of experts who evaluate the object. When its value is larger, more experts give full marks to the object; that is, the relative importance of the object is larger:

$$K_j^1 = \frac{m_j^1}{m_j}. \quad (3)$$

The evaluation level of object j: S_j is the object evaluation level, R_{ij} is the rank of expert i's score c_{ij} for subject j ranked among all the scores ($c_{i1}, c_{i2}, \cdots c_{ij} \cdots, c_{in}$) of this expert i, and $m_j m_j$ is the number of experts who have evaluated object j. The smaller the evaluation level and the smaller the object, the greater its relative importance, which can be obtained by the following formula:

$$S_j = \sum_{i=1}^{m_j} R_{ij}. \quad (4)$$

The degree of coordination of expert opinion can be expressed by the coefficient of variation. The coefficient of variation is an important index to measure the relative dispersion degree of experts' evaluation, which reflects the degree of coordination of experts' evaluation of the relative importance of each object and is also the degree of expert consistency. D_j is the variance of all experts' evaluations of object j representing the degree of dispersion of experts. The standard deviation of the evaluation of j is as follows:

$$\sigma_j = \sqrt{D_j} = \sqrt{\frac{1}{m}\sum_{i=1}^{m_j}\left(c_{ij} - M_j\right)^2}. \quad (5)$$

The formula for the arithmetic mean of j is as follows:

$$M_j = \frac{1}{m_j}\sum_{i=1}^{m_j} c_{ij}. \quad (6)$$

The coefficient of variation is the ratio of the standard deviation of all experts' assessments of j to the arithmetic mean. The lower the coefficient of variation, the higher the degree of consensus among experts. The coefficient of variation of evaluation object j is as follows:

$$V_j = \frac{\sigma_j}{M_j}. \quad (7)$$

(1) Experts' evaluations and predictions are based on intuitive but not rigorous data and arguments, so the results are often unstable, unfocused, and uncoordinated.

(2) Experts will have, one way or another, a difference in experience, knowledge, judgment criteria, psychological state, and so on, so the evaluation angle and evaluation standard of the survey object will also be different.

(3) Experts often consider problems and assessment objects from the perspective of their own profession and inevitably have professional limitations and prejudices.

3.2. Dynamic Model of Raw Material Supply Chain. The raw material supply chain inventory can be represented by control variables, supply, and actual quantities, among which $X_{1,k+1}$ is the supplier's inventory at time k. There are n-dimensional state control variables. $U_{1,k}$ is the supply chain at time k and $V_{1,k}$ is the actual quantity supplied to the manufacturer at time k. The basic state equation is as follows:

$$X_{1,k+1} = X_{1,k} + U_{1,k} - V_{1,k}, \quad K = 1, 2, \ldots, n. \quad (8)$$

In the dynamic model of raw material inventory management, the equation is as follows:

$$X_{2,k+1} = X_{2,k} + P_k - V_{2,k}, \quad K = 1, 2, \ldots, n. \quad (9)$$

The raw material inventory cost objective function is as follows:

$$M_1 = \sum_{k=0}^{N} q_{11}^T X_{1,k}, \quad K = 1, 2, \ldots, n. \quad (10)$$

Restrictions are as follows:

$$\begin{aligned} q_{11}^T &\geq 0, \\ X_{1,k} &\geq X_1^0. \end{aligned} \quad (11)$$

The raw material transportation cost is as follows:

$$M_2 = \sum_{k=0}^{N} r_{11}^T V_{1,k}. \quad (12)$$

Constraint adjustment is as follows:

$$r_{11}^T, V_{1,k} \geq 0. \quad (13)$$

The inventory turnover rate is the most important indicator to measure the quality of inventory management level in the supply chain. R is the inventory turnover rate, $\overline{S}$ is the average value of raw materials used in the last month, $\overline{T}$ is the average value of inventory in the last month, and DIO is the number of inventory turnover days:

$$R = \frac{\overline{S}}{\overline{T}},$$
$$\mathrm{DIO} = \frac{365}{R}. \tag{14}$$

In the exponential smoothing formula, t represents the time of the current cycle, A_t represents the exponential smoothing constant, Y_t represents the actual value in the t period, and represents the predicted value in the t period.

The desired result can be predicted with less data. Exponential smoothing is a time series analysis and prediction method developed on the basis of the moving average method. It is compatible with long-term and moving averages. However, it only gives a gradually decreasing degree of influence. When data disappear, they assign a weight that gradually approaches zero, namely predicting the future of the phenomenon by calculating the exponential smoothing value and matching some predictions of the time series model:

$$Y_{t+1} = aA_t + (1 - a)Y_t. \tag{15}$$

The supply qualification index refers to the inspection of incoming materials, which can be used as an important indicator to measure the quality of incoming materials. It can be calculated separately for different manufacturers to evaluate the qualifications of suppliers, and it can also be used to calculate the quality of supplied goods in different delivery times or cycles. The higher the delivery success rate, the stronger the quality control of the supplier's products. V stands for eligible freight, X for eligible freight, and N for total purchase quantity. The formula is as follows:

The supply qualification rate refers to the inspection qualification of incoming materials, which can be an important indicator to measure the quality of incoming materials. It can be calculated separately for different suppliers to evaluate the qualification of suppliers and can also be used to compare the supply in different periods or supply cycles. The higher the supply pass rate, the stronger the supplier's product quality control:

$$V = \frac{X}{N} * 100\%. \tag{16}$$

It is necessary to save money when purchasing, but it is also necessary to ensure quality. The greater the number of key materials, the greater the cost savings of this part of the order, indicating that the cost of purchasing cost control is better. Let G represent the purchase cost savings rate, R the actual purchase price, and J the benchmark purchase price. The formula is as follows:

$$G = \left[\frac{(T - J)}{J}\right] * 100\%. \tag{17}$$

Select qualified suppliers through supplier selection, and select suppliers through a combination of qualitative and quantitative methods. The inspection-free rate of incoming materials can reflect the maintenance of the relationship with suppliers. The closer the quality, the more confident the cooperation. Use L to represent the inspection-free rate of incoming materials, Z to represent the number of types of incoming materials exempted from inspection, and C to represent the number of product types supplied by strategic suppliers:

$$L = \left(\frac{Z}{C}\right) * 100\%. \tag{18}$$

4. Computationally Intelligent Raw Material Supply Chain Optimization and Analysis

4.1. Selection of Quality Improvement Factors for Raw Material Supply System. The severity of the influencing factors is obvious. According to Plato's principle, find the most important factor from the twelve factors. The largest is the minority, and the second is the majority. Factors with an 80% accrual rate are considered critical factors, and factors with a 20% accrual rate are considered critical secondary factors. More than 80% of them include the economic and technical environment, the realization of the functions of the procurement department, the stability of prices, the technical level, the awareness of system management, the product qualification rate, the quality inspection and testing, and the timeliness of problem handling. The three weights of situation, procurement efficiency, and cooperation compatibility account for 80%, which are important factors for improving the supply of raw materials, as shown in Figure 2.

4.2. Analysis of Key Indicators of Suppliers. By taking a representative company as an example, a computationally intelligent raw material supply chain analysis is carried out, and strategic suppliers are selected by applying the Delphi method to suppliers in the raw material supply process of the company. The quality inspection and the weights of test situation, price qualification rate, and technical level are relatively higher than other indicators, and the corresponding weights are 0.15, 0.25, and 0.15, respectively, as shown in Figure 3.

In the quality inspection and test situation, Supplier A is advanced and complete, Supplier B is strict and complete, and Supplier C is strict and good. In the strict pass rate, Supplier A has the highest pass rate, 97%. The lowest is Supplier C, with a pass rate of 94%. In terms of price stability, Supplier A is relatively stable, Supplier B is stable, and Supplier C is relatively stable. In terms of the timeliness of problem handling, Supplier A is relatively stable within 24 hours, Supplier B is within 48 hours, and Supplier C is within 48 hours. In the cooperation compatibility situation, Supplier A, Supplier B, and Supplier C are strong. In the financial situation, Supplier A is good, Supplier B is better, and Supplier C is better. In the economic and technological environment, Supplier A, Supplier B, and Supplier C are developed, as shown in Table 1.

The procurement team sets the performance score and corresponding status for each key indicator according to the 5-point system. Performance score 5 indicates good; performance score 4 indicates the description is good;

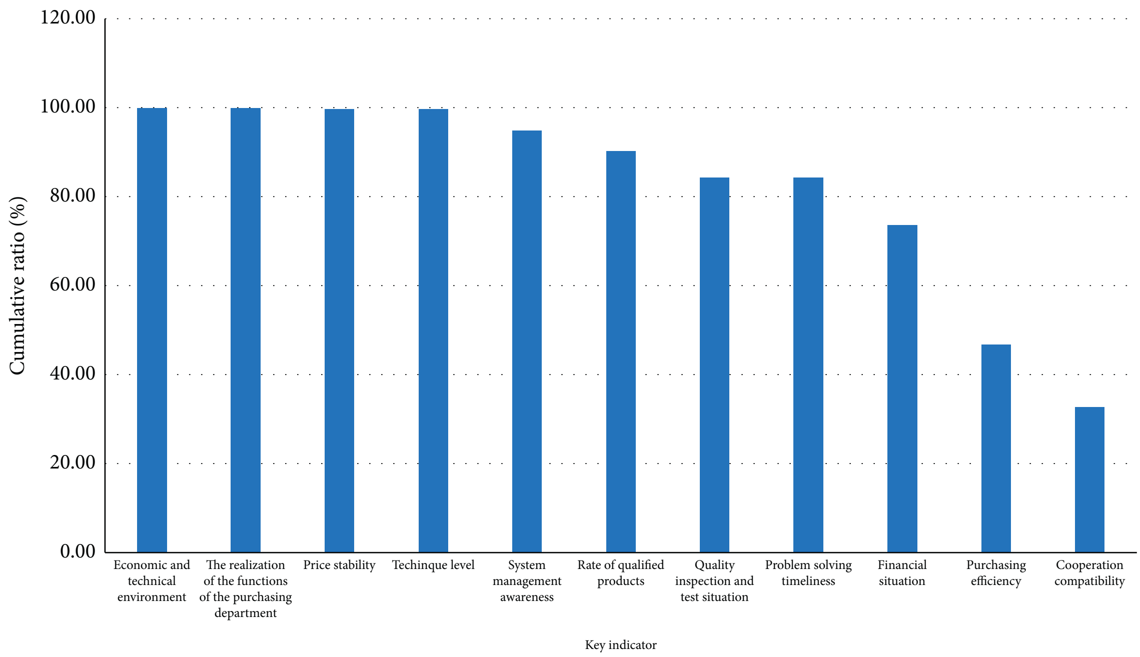

Figure 2: Importance screening of quality improvement factors in the raw material supply system.

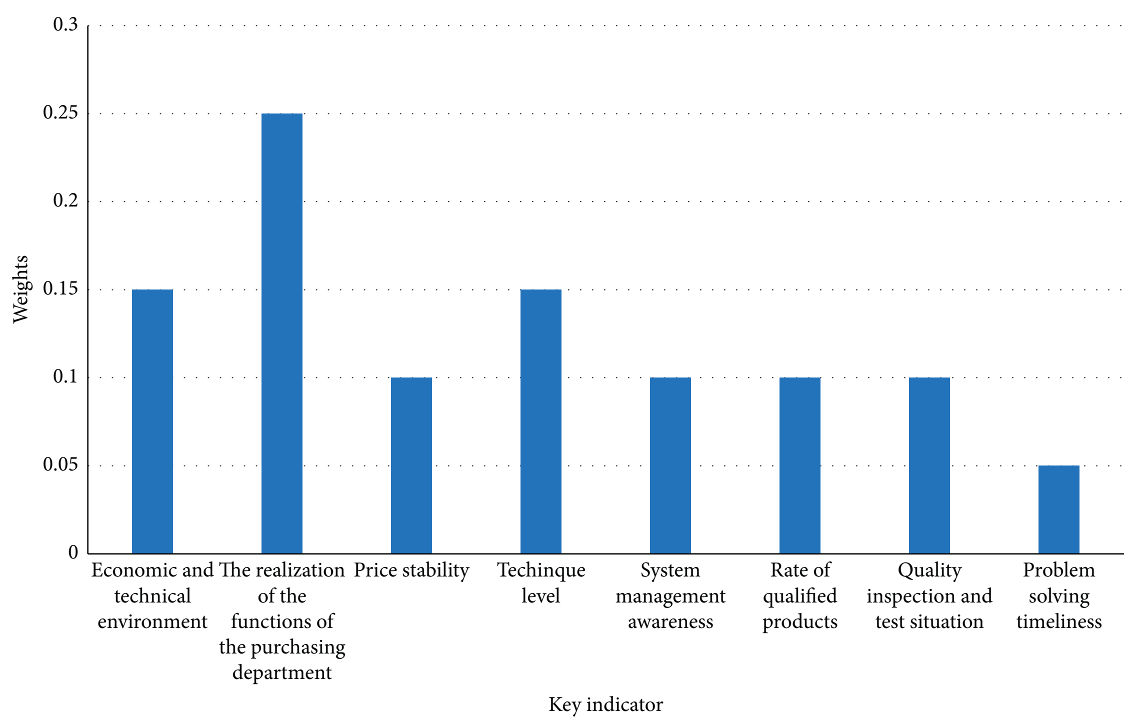

Figure 3: Weights of key indicators.

performance score 3 indicates the description is average, the performance score is average; a value of 2 indicates poor performance; and a performance score of 1 indicates poor performance, as shown in Table 2.

Aggregate the scores of participants, assuming the final average performance score, as shown in Table 3.

By multiplying the scores of the key indicators of suppliers by the corresponding weights and adding up the weights, the final total supplier score is obtained. It can be seen from the table that Supplier A has the highest total score, and the t-value is 4.4; Quotient B, t has a value of 4; and Supplier C, t has a value of 3.55. Because the condition set by the procurement team is the highest t-value score, the supplier with the highest score can be selected as the strategic supplier. In other words, Supplier A can be selected as a strategic supplier. For the selected strategic suppliers, the company should provide

Table 1: Supplier key indicators, corresponding weights, and data.

Key indicator	Corresponding weights	Supplier A	Supplier B	Supplier C
Economic and technical environment	0.15	Advanced and complete	Strict and complete	Strict and better
The realization of the functions of the purchasing department	0.25	97%	96%	94%
Price stability	0.1	Relatively stable	Stable	Relatively stable
Technique level	0.15	Okay	Better	Okay
System management awareness	0.1	Within 24 hours	Within 48 hours	Within 48 hours
Rate of qualified products	0.1	Very strong	Very strong	Strong
Quality inspection and test situation	0.1	Okay	Better	Better
Problem-solving timeliness	0.05	Developed	Developed	Developed

Table 2: Key indicator weighted index evaluation model performance score scheme.

Performance score	Illustration
5	Very good
4	Better
3	General
2	Poor
1	Very poor

Table 3: Supplier key indicator scores.

Key indicator	Supplier A	Supplier B	Supplier C
Economic and technical environment	5	4	3
The realization of the functions of the purchasing department	5	5	4
Price stability	3	4	3
Technique level	4	3	4
System management awareness	4	3	3
Rate of qualified products	5	5	4
Quality inspection and test situation	4	3	3
Problem-solving timeliness	4	4	4

Table 4: Total supplier score.

Evaluate	Supplier A	Supplier B	Supplier C
t-value	4.4	4	3.55

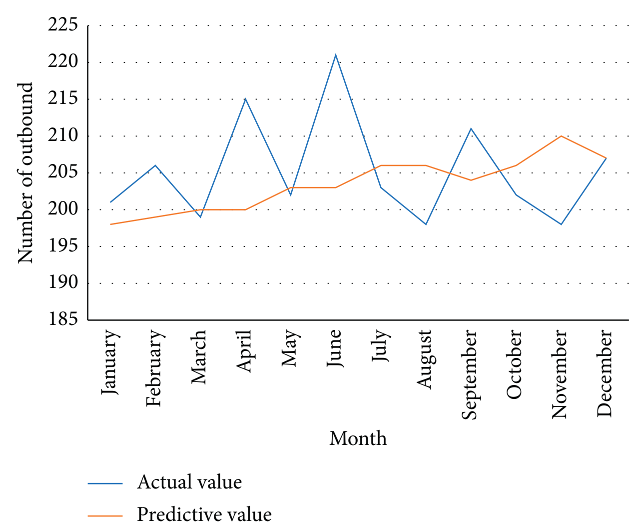

Figure 4: Raw material supply forecast.

various support, such as merging procurement logistics, preferential payment for goods, and information sharing, in exchange for the supplier's stocking support, and after-sales premium treatment, as shown in Table 4.

Through the analysis, it is concluded that the weights of quality inspection and testing, the price qualification rate, and the technical level are relatively high compared to other indicators. Multiply the scores of the key indicators of the supplier by the corresponding weights, and add up the weights to obtain the final result. Supplier A has the highest overall score. Through the analysis of key indicators, the supplier with the paramount score can be chosen as the strategic supplier.

4.3. Raw Material Supply Trend Adjustment Index Smoothing Method. Figure 4 shows that most of the actual values are above the predicted values. By comparing the predicted monthly outbound numbers with the actual outbound numbers, the actual value in January was 201 and the predicted value was 198; the actual value in February. 206, and the predicted value was 199; the actual value in March was 199 and the predicted value was 200; the actual value in April was 215 and the predicted value was 200; the actual value in May was 202 and the predicted value was 203; the actual value in June was 221 and the estimated value was 203; the actual value in July was 203 and the estimated value was 206; the true value in August was 198 and the estimated value was 206; the true value in September was 211 and the estimated value was 204; the true value in October was 202 and the estimated value was 206; the true value in November was 198, and the estimated value was 210; and the true value in December was 207 and the estimated value was 207, as shown in Figure 4.

The error rate between the estimated and true values is relatively small, and the predicted value can be obtained by calculating the supply of raw materials to avoid the waste of raw materials, reduce the cost and expense, and inventory the raw materials more reasonably.

Figure 5 shows that the prediction error rate is 9%, and the error rate is relatively small. The largest forecast error rate was in June, with a forecast error rate of 8.14%; the

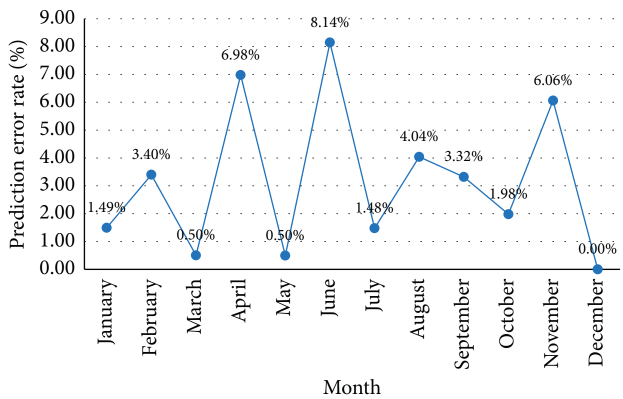

Figure 5: Prediction error rate.

smallest was in December, with an error rate of 0. In January, the forecast error rate was 1.49%; the February forecast error rate was 3.4%; the March forecast error rate was 0.5%; the April forecast error rate was 6.98%; the May forecast error rate was 0.5%; the July forecast error rate was 1.48%; the August forecast error rate was 4.04%; the September forecast error rate was 3.32%; the October forecast error rate was 1.98%; and the November forecast error rate in November was 6.06%, as shown in Figure 5.

5. Conclusion

Through the analysis of the weight value level of the influencing factors, it is obtained that the economic and technical environment, the realization of the procurement department's functions, the stability of prices, the technical level, the awareness of system management, the product qualification rate, the quality inspection and testing, and the timeliness of problem handling are important indicators. Financial situation, procurement efficiency, and cooperation compatibility are important factors in improving the supply of raw materials. The Delphi method is used to select the strategic suppliers for the corresponding weights of the key indicators of suppliers, and the supplier with the highest score after weighting can be selected as the strategic supplier. The raw material supply trend-adjusted exponential smoothing method can predict the raw material supply value to reduce the loss of materials. Through this similar computing intelligence, the supply chain can be optimized to bring benefits to the enterprise and finally realize the standardization of the procurement process, the optimization of the supplier group, the sharing of procurement information, the supervision of the procurement process, the reduction of procurement costs, the improvement of the level of procurement intelligence, the division of tasks and performance assessment, the goal of win-win with suppliers.

Data Availability

The experimental data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declared that they have no conflicts of interest regarding this work.

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